

AI-Enabled Price Negotiation Chatbot Using Ensemble Classifier For E-Commerce Platform

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Abstract: The high rate of growth of e-commerce site has heightened the necessity to implement smart and dynamic pricing systems that can adjust to varying customer tastes without losing the profitability of the sellers. The conventional fixed and rule-based approach to pricing is not capable of dynamically interacting with its customers and cannot respond to the negotiation-based buying behavior. This article aims to overcome this drawback by introducing a price negotiation chatbot based on AI that applies the principles of natural language processing and an ensemble classification model to facilitate price negotiation in real-time, in the form of a conversation, during online retail processes. The system suggested combines intent identification, sentiment analysis, and user behavioural modeling to derive valuable negotiation characteristics out of customer interaction. All these characteristics undergo processing by a pool of machine learning classifiers to identify the best negotiation behaviors, i.e. accept, counteroffer, or reject. Dynamically generated price recommendation strategy is then used to produce context sensitive counteroffers but within the business constraints which may be profit margins and inventory levels. Based on the experiments carried out on simulated e-commerce negotiation datasets, it can be proved that, compared to single classifiers, the suggested ensemble-based methodology is more accurate, has better F1-score, and negotiation success rate, as well as produces more deals. Findings also show better equilibrium between profit and customer satisfaction of the sellers as well as the shortest response latency and the system is appropriate to be used in real-time. The results present the strengths of the ensemble learning and conversational intelligence in automated pricing technology and present high potential of application to large scale e-commerce systems in the future.

Keywords: AI-Enabled Chatbot, Ensemble learning, Deep learning, Classifiers, E-commerce platform, Negotiation-based behavior.

1. Introduction

The high growth of e-commerce platforms has radically changed the world retail ecosystem by allowing digital transfer of transactions, a wide variety of products, and customized shopping experiences. As competition levels are rising among online retailers, pricing has become an essential strategic issue affecting consumer decisions, the rate of conversion, and consumer loyalty. Conventional e-commerce pricing strategies are mainly based on fixed pricings or discount policies that are not very dynamic to customer heterogeneity, market demand changes and buying situations. Consequently, the contemporary e-commerce platforms are also becoming inclined towards smart, data-intensive pricing processes which can interact with customers as well as maximizing the business goals [1]. Negotiation has always been an inherent part of trade especially in real-

life marketplaces whereby buyers and sellers bargain to agree on mutually accepted prices. Nevertheless, all online stores do not have interactive negotiation functions because of the problem of scales, the complexity of operations, and the constraints of a human-driven negotiation process. Computationally efficient though fixed pricing models minimize customer interaction and can result in profit margin and user-satisfaction maximization opportunities. This leads to an increased demand of automated negotiation systems that can simulate human-like bargaining behavior and can be very efficient when used in digital marketplaces at large scale [2].

The recent breakthrough in artificial intelligence (AI), machine learning (ML), and natural language processing (NLP) has also enabled the creation of intelligent conversational agents which can communicate with users in real time. Chatbots have become an essential element of conversational commerce, allowing automated customer service, product proposals, and transactional services [3]. Whereas current e-commerce chatbots do a good job to respond to queries and lead the user through the purchasing processes, their functionality in the dynamic price negotiation is not yet well-explored. The vast majority of implemented chatbots operate based on fixed scripts or even basic decision-making algorithms, which restricts their flexibility towards the complex negotiation conditions that require different user motives and emotional contexts, and transaction and buying history. Dynamic pricing methods are widely researched concerning the airline ticketing process, ride-hailing services, and hotel booking webpages [4]. The strategies normally use demand projections, time pricing and inventory restrictions to maximize prices. Nevertheless, seller-centric models are mostly this type and are not used in direct interaction with users. Conversely, price negotiation brings about a two-way decision-making system where the system needs to take into consideration user offers, set acceptable levels of profits to be made and create a counteroffer that is context sensitive [5]. This issue is even more complicated in the online world where the actions of the users are unpredictable, communication is performed in a natural language, and the results of negotiations need to be calculated immediately (Figure 1).

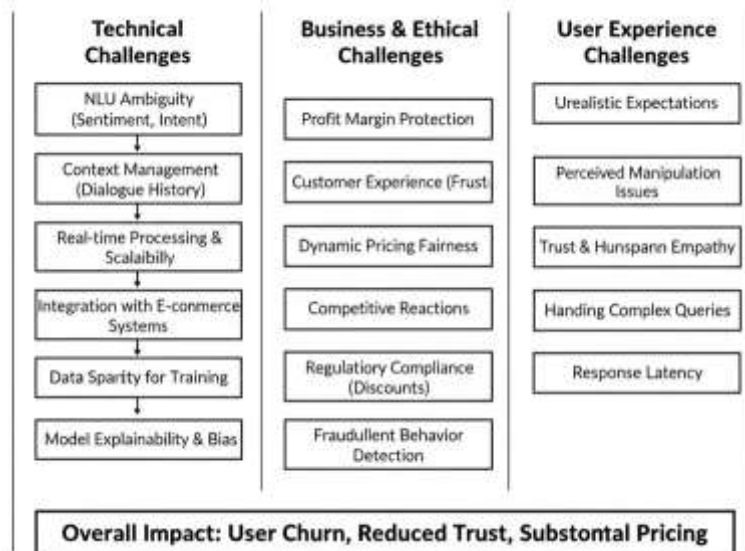


Fig.1 Challenges in Price negotiation chatbot

The proposed model with conversational interfaces is to overcome these challenges as artificial intelligence-powered negotiation systems are designed to tackle these issues. In this regard, the classification models that are supervised by learning have proven to be

effective in identifying the actions during negotiation like accepting an offer, rejecting an offer, or making a counteroffer. Nonetheless, when one relies on a single classifier, he is likely to make suboptimal choices based on model bias, overfitting, or sensitivity to noisy data. E-commerce negotiation space is a dynamic environment that is always uncertain and its users are dictated by psychological factors, sentiment, urgency and external market conditions [6]. These intricacies require effective decision-making models that can generalize on a variety of situations in negotiation. Ensemble learning has turned out to be a major paradigm in machine learning, with better predictive performance due to the use of several base classifiers. Ensemble models combine the strengths of various learning algorithms and decrease the variance and bias and improve the generalization capability. The bagging technique, boosting, as well as stacking techniques have exhibited better performance in different areas such as fraud detection, recommendation, and financial forecasting. Although their effectiveness has been demonstrated, ensemble classifiers are not widely used in conversational negotiation systems, and especially in real-time e-commerce systems where the accuracy of decisions has a direct effect on revenue and customer experience. The other important issue in automated price negotiation is that it is difficult to know what is happening and the sentiment of the user when engaging in conversations. Customers can indicate that they are willing to pay indirectly which is determined by their emotional responses like urgency, frustration or even satisfaction [7]. Chatbots are also able to infer semantic and emotional aspects of user utterances by using natural language processing techniques, which is an important indicator of negotiation strategy development. The combination of sentiment-conscious decision-making and classification based on machine learning can bring great improvements to the outcomes of negotiations since it will lead to the ability to respond to situations with specific context-aware reactions as opposed to the response to rigid rules.

The contemporary consumers are getting more demanding when it comes to customized communication with the online sources [8]. Customization of price bargaining necessitates the exploitation of past user information comprising frequency of purchase, price responsiveness, loyalty, and browser within the algorithm. By adding these behavioral characteristics to the negotiation model, the system will be able to adjust the offers dynamically so that it can satisfy the customer and still make a profit. Nevertheless, creating such a system is associated with the problems of sparse data, cold-start users, and fairness, especially regarding the prevention of discriminatory pricing. Another urgent issue facing e-commerce platforms of large scale is the scalability of negotiation chatbots. Negotiation done by human intervention is non-practical because of high operation cost and scarcity. Automated negotiation agents must consequently be able to act independently, support thousands of ongoing dialogs as well as produce decisions at a low latency rate. This will require light but precise machine learning models with the capability to make real-time inferences [9]. Well-designed and optimized ensemble classifiers provide a good trade-off between computational performance and decision resilience.

The price negotiation problem is defined formally and is formulated as a supervised classification problem. The suggested formulation includes economic constraints, user behavior and conversational context which allow making intelligent and real time negotiation decisions in e-commerce settings. E-commerce price negotiation is a process that includes inter-working parameters that determine the result. In comparison with conventional fixed prices, negotiation implies constant assessment of the buyer proposals in terms of business and situational conditions. The system models suggested representing negotiation in the form of a structured decision problem with the parameters of pricing, behavior, and language [10]. The most important negotiation parameters can be mentioned as product-related characteristics, constraints imposed by

the seller and user-related variables. These parameters allow the system to strike a balance between profitability and customer engagement as well as remain fair and consistent in various negotiation sessions.

The first price is the base price of a product that is posted in the e-commerce site. This is the price at which a negotiation process commences, and this price is influenced by factors like the cost, market demand, pricing of competitors and promotional strategies. The first price is also a price ceiling of negotiation and a benchmark in assessing the offers of buyers. The minimum seller price is the lowest possible price at which the seller is prepared to transact at without making any losses. This parameter will include cost of product, margin of profit desired, cost of logistics and inventory consideration. It is a firm limit in negotiation process whereby offers generated are economic. The user price that is offered in the process of negotiation is known as the buyer offer. The buyer offers can differ significantly basing on the user price sensitivity, perceived product value, urgency, and previous experience on the platform. The system also analyzes the buyer offer against the first and lowest seller prices to know whether it is possible and the way to negotiate. User intent is defined as the purpose behind the interaction which is conveyed in the conversation [11]. With regards to price negotiation, the intents might be requesting a discount, making a particular offer, clarification and dissatisfaction with price. The detection of intent must be accurate, since this will help in forming the strategy of the negotiation, and the formation of the response.

Sentiment is a feeling of user messages e.g. positive, neutral, or negative. Sentiment indicators are useful in giving an indication of user willingness to negotiate, urgency and satisfaction. In the case of a negative sentiment, it can signify that it is price resistant whereas a positive sentiment can signify that it will get accepted at a higher rate. The addition of sentiment into the negotiation model allows contextual and empathetic decision-making. User purchase history contains the historical data of the purchases, which include frequency of purchases, the average value of orders, the usage of the discounts, and the loyalty. These behavioral qualities can give us a clue as to the price sensitivity and value of the users over the long term. Users who have a high lifetime value can be provided with more flexible results of the negotiation to retain. All the parameters of negotiation are converted into a structured feature vector and are then used in machine learning-based decision-making. The numerical characteristics like price ratios, discount percentage, and frequency of purchases are normalized so that consistency can be attained. Categorical variables, such as user intent and sentiment category, are coded with the help of proper encoding methods. To include the nonlinear relationships, feature interactions are added, including the ratio of buyer offer to initial price or sentiment-weighted discount tolerance. This overall feature modeling allows the classifier to assess negotiation situations in totality as opposed to using only price-based limits. The decision to be made in the negotiation is developed as a multi-classification problem. Given a feature vector of the prevailing negotiation state, the classifier will make predictions as to one of the following classes:

- Accept: The buyer offer becomes acceptable and profitably and strategically sound and is accepted as in the current form.
- Counter: The buyer offer is lower than acceptable levels but suggests the possibility of negotiation, therefore, a counteroffer.
- Reject: The buyer offer does not satisfy minimum restrictions, or it does not represent high negotiation viability and leads to rejection.

The classification task of formulating negotiation facilitates real-time, stable and interpretable decision-making. Such a strategy is especially applicable in the context of e-commerce where predictability, scalability, and user experience matter. This construction provides a systematic basis on the proposed ensemble-based negotiation model that can

be used in the intelligent, adaptive, and economically viable price negotiation in conversational e-commerce systems.

Although the research on dynamic pricing, conversational AI, and automated negotiation has significantly been conducted, the existing research tends to focus on these aspects separately. There is little literature on how ensemble learning can be used in conjunction with conversational negotiation models specifically designed to e-commerce websites. Additionally, most of the previous methods focus on negotiation agents that are based on reinforcement learning, and that need a great number of training cycles and that can be rather unstable in the initial stages of their learning. Conversely, supervised ensemble classifiers present a more regulated and interpretable framework of decisions and so they are suited to the real-world implementation where predictability and transparency are paramount [12]. The current article suggests an AI-based price negotiation chatbot, which can be used to aid in intelligent decision-making in online shopping settings with the help of an ensemble classifier. In the suggested system, the combination of natural language understanding, modeling user behavior, and ensemble-based classification is used to identify the best negotiation actions in a real-time setting. The chatbot analyses customer offers based on various attributes, such as linguistic attributes, sentiment polarity, historical purchases, and price limits. The output of the ensemble model determines whether to accept the offer, create a counteroffer or turn down the negotiation whilst keeping pre-existing profit margins.

The main objective of the research will be the promotion of the effectiveness of negotiations and user interaction without undermining the sustainability of the businesses. Through the ensemble learning model, the proposed system will enhance the accuracy of the decision as opposed to single-model classifiers and must be robust to various negotiation conditions. Also, conversational interface will create a more interactive and human-like shopping experience, which may lead to higher customer confidence and allegiance to the platform. First, it is a detailed design of a price negotiation chatbot based on AI to fit e-commerce websites. Second, it presents a decision framework using ensemble classifier that incorporates several machine learning models to enhance the negotiation results. Third, it presents the empirical assessment of the suggested system based on the adequate performance measures proving that it is effective in terms of the negotiation success rate, the profitability, and the user satisfaction. The proposed solution can reduce the major drawbacks of the traditional pricing models and the current solutions to chatbots through offering automated, adaptive, and scalable price and negotiation. The study is a part of the dynamic context of AI-based online retail because it provides a viable and solid model of interactive negotiation of prices, which has a considerable impact on the academic community and the business.

II. Literature Review

The fast development of AI, data analysis, and conversation interfaces have had a major impact on the pricing policies and customer communication processes within the e-commerce platforms. The current section summarizes past studies pertaining to the price negotiation systems, conversation chatbots in online shopping, ML for pricing and decision support, ensemble learning, and research gaps that are found critical and driving the proposed work. Initial e-commerce price systems were majorly based on the traditional models that include fixed prices, bargaining, and other mechanisms based on the auction. Such auction models as English, Dutch, and Vickrey have been well researched and applied to platforms like eBay to achieve price discovery by competitors bidding [13]. Experiments in this field indicated that the revenue of those who sell products through auction-based pricing can be enhanced and market efficiency achieved, especially when the demand of buyers is not known or homogeneous. Prices based on bargaining are

based on the way humans negotiate with each other, and hence parties can make and take turns in offering and accepting until a deal is made. Some of the studies suggested automated bargaining models based on preset concession policies, price variations depending on time, and utility-based decision-making models. These systems were usually based on mathematical expressions of buyers and sellers' utility, reservation price and negotiation time constraint. The traditional bargaining [14] and auction-based models have serious constraints in the contemporary e-commerce settings. First, they frequently need direct user engagement and long interaction duration that can yield a bad experience to users in the context of online shopping where the speed is crucial. Second, the models are not flexible to a particular customer behavior, sentiment and history of purchases. Third, they are mostly seller-oriented and do not integrate conversational intelligence thus they cannot connect with users effectively.

A. Automated Negotiation Agents

To address the limitations of the human-mediated negotiation, which are scalability, researchers proposed automated negotiation agents that allow the representation of the interests of buyers or sellers. Such agents normally work with a predefined negotiation protocol and strategy, including concession based, heuristic based or game theoretic strategies [15]. Several multi-agent negotiation systems had been suggested to model the competitive market environments and maximize the negotiation process. Although automated negotiation agents increased scalability and consistency, their performance was limited by strict rules and sturdy assumptions on the opponent behavior. Most systems used rational agents that are fully informed which is hardly the reality in real e-commerce situations. These agents also had problems coping with natural language interactions, emotional indications and ambiguous user intent. More recent works considered learning-based negotiation agents with reinforcement learning to change strategies with time. Despite this, the techniques are promising but involve long training episodes, reward-sensitive and can be unstable in the initial stages of deployment [16]. Such constraints limit their direct use in the commercial e-commerce systems where reliability and predictability are very important.

Chatbots are an inseparable part of a modern e-commerce, mostly used as a customer support system, order tracking, as well as product recommendation. Initial chatbot implementations were largely rule based and based on pre-created decision trees, key word matching and scripted responses. These systems were highly predictable and controllable but not flexible and understanding. The chatbots based on rules are useful to deal with common questions and workflows, but they fail to work effectively in more complex and dynamic communication, including price negotiation [17]. They are incapable of adapting to other user behavior and negotiation tactics due to their inability to generalize outside set rules. Chatbots powered by machine learning and NLP algorithms are a great improvement compared to rule-based systems. These chatbots use intent classification, entity recognition and contextual modeling to produce more natural and personalized responses. Researchers have reported that chatbots because of AI have a vastly positive effect on customer engagement, customer satisfaction and customer conversion in online shopping platforms.

B. NLP-Driven Conversational Commerce Systems

Chatbot Conversational commerce systems build upon chatbot capabilities by providing end-to-end shopping experiences by using natural language interaction. It was found that previous studies had investigated NLP pipelines that use tokenization, semantic parsing, intent detection, and sentiment analysis to interpret user queries. Several studies indicated the need to use sentimental chatbots in the retail sector and showed that

emotional states like frustration, urgency, or enthusiasm affect buying decisions. Sentiment analysis as part of chatbot response has been demonstrated to increase perceived empathy and trust [18]. Although these have been developed, most conversational commerce systems are aimed at information retrieval and recommendation as opposed to price negotiation in an interactive environment. Interactions connected to price are generally restricted to revealing of discounts or promotional packages, and there is little flexibility on either user counteroffers or bargaining interest. This shows a definite lack of literature in intelligent, negotiation-capable conversational agents.

The application of machine learning in e-commerce has been highly used in pricing optimization and decision support. Linear regression, decision trees, random forests, support vector machines, and gradient boosting are supervised learning models aimed at predicting and estimating the demand elasticity, optimal prices, and customer ready to pay. Several researchers showed that under supervision, ML models perform better than the traditional econometric models in the process of estimating nonlinear relationships between price and demand and contextual features [19]. Such models especially work well in case of historical data of transactions and proper forecasting is made on the probability of a price to be accepted. Supervised classifiers have been applied in negotiation situations to define offers as acceptance, rejection or counteroffer classes based on properties like offer value, time pressure and user profile properties. Nevertheless, most existing methods utilize just single-model classifiers, therefore, being susceptible to overfitting and decreased generalization in the real, noisy world.

C. Reinforcement Learning versus Classification-Based Negotiation

Reinforcement learning (RL) has attracted interest as one of the most effective paradigms of the step-by-step decision-making in the context of negotiation systems. The RL-based agents discover the best approaches based on trial-error interactions, which maximize the long-term rewards. Several studies stated that RL agents could learn advanced negotiating strategies without necessarily modeling agent behavior. However, the RL-based negotiation systems have been associated with realistic difficulties in the implementation of e-commerce. Training involves huge amounts of interaction data, and this data might not be easily available [20]. Also, searching in the process of learning might result in undesirable negotiation results, which affect user experience negatively. On the contrary, classification-based negotiation models are more stable and interpretable. The classification-based systems can use past data to draw dependable and predictable decisions by framing the negotiation as a supervised decision problem. Nevertheless, both the quality of features and the robustness of the model is essential to their performance, which encourages applying the ensemble learning methods.

Ensemble learning involves using a combination of several base learners to come up with a more reliable and stronger predictive model [21]. Bagging methods like the Random Forests minimize variance by fitting several models on bootstrapped data samples. AdaBoost and Gradient Boosting algorithms are boosting algorithms aimed at improving performance by prioritizing hard instances to classify. The methods of stacking use a meta-learner to pool the predictions of heterogeneous models. Experimental studies in different fields of application, including fraud detection, medical diagnosis, financial forecasting, and others, have shown in all cases that ensemble models result in more accurate, more stable, and more generalized results, compared to individual classifiers. Ensemble techniques are especially good in uncertain, noisy, and complicated feature interactions environments. E-commerce negotiation is characterized as uncertain because of the variability in customer behavior, unavailable information and context. Ensemble classifiers help to overcome these issues by combining a variety of decision views, and no

one model relies on its assumptions. Multiple studies have emphasized that ensemble models are more robust to concept drift, which also affects the environment of e-commerce where consumer behavior changes as time progresses [22]. Besides, ensemble methods can use linear and nonlinear models, representing a larger evidence base of decision patterns. Although these benefits are present, the use of ensemble learning in conversation negotiation systems is still minimal. Most of the available literature uses ensemble models to solve a backend optimization pricing or demand prediction, as opposed to the real-time, end-user-facing negotiation decisions.

D. Research Gaps

According to the literature review, there are several critical research gaps that can be outlined:

- Current e-commerce pricing models are mostly based on either the point-of-sale pricing or the seller based dynamic pricing models, which are less interactive and personalized.
- The automated negotiation agents usually have fixed rule-based or reinforcement learning approaches that are not very easy to implement efficiently in real-world systems.
- Majority of retail chatbots are not intelligent in the negotiation process and rather only do customer support and product discovery.
- Single-model machine learning models are used to pervade negotiation decision-making, which restricts strengths in uncertain and noisy settings.
- Ensemble learning has not been studied in conjunction with NLP-based conversational negotiation systems.
- There are not much research concerning the trade-off of customer satisfaction, profitability, fairness, and scalability in real-time in automated price negotiation.

The gaps point to the necessity of an AI-powered price negotiation chatbot with conversational intelligence and ensemble-based decision-making. Discussion of these weaknesses is the main point of the suggested framework that is designed to provide strong, flexible, and adaptable negotiation services on the modern e-commerce platforms.

III. System Architecture

This section mainly focusses on the suggested system structure of the AI-based price negotiation chatbot that will be implemented on e-commerce websites. It is based on an architecture that focuses on modularity, scalability and real-time decision-making capabilities, facilitating the integration of the architecture with existing e-commerce infrastructures [23]. The system can be used to enable dynamic and interactive price negotiation by leveraging conversational intelligence and ensemble-based machine learning, whilst considering the business limit of profitability, fairness, and latency requirements.

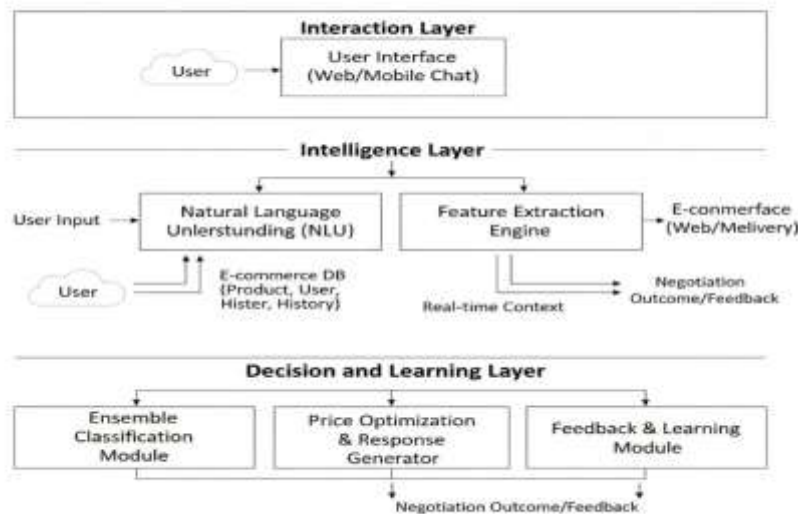


Fig.2 Proposed System Architecture

The suggested framework (Figure 2) is based on the layered and modular structure that separates the interaction with the user, conversational understanding, decision intelligence, and pricing strategy development. This division provides the flexibility, maintainability, and suitability to the changes in the business needs. At a top level, the system has three main layers as follows: Interaction, Intelligence and Decision and Learning Layer. The Interaction Layer manages all communication that is user facing in the form of a conversation interface. The Intelligent Layer takes input in the form of natural language understanding and converts it into a structured format. The Decision and Learning Layer interprets negotiation offers with ensemble classifiers, produces optimized responses and does not cease to improve decision strategies with feedback. The chatbot is real-time, and it allows the customers to bargain when shopping or at the check-out counter. In contrast to other methods of providing a discount (which are static), the system dynamically analyzes every negotiation request with references to linguistic cues, user behavior, past transaction information and pricing restrictions. The architecture allows the chatbot to act like a human during bargaining and to run on a large scale. In the interaction flow, the process starts when an individual triggers a chat with the chatbot, usually in a chat interface, which is incorporated in the e-commerce site. The user can demand a discount, counteroffer or give price intended intent in natural language.

- **User Input:** The user enters a textual message that communicates his price negotiation intention, like asking to have the price reduced or placing an offer.
- **Chatbot Processing:** The chatbot accepts the message then sends the same to the Natural Language Understanding module to analyze the message semantically.
- **Intent and Feature Processing:** Feature extraction is then sent to the Feature Extraction Engine where conversational, behavioral and contextual attributes are fused.
- **Decision Evaluation:** The Ensemble Classification Module assesses the offer and predicts the type of the negotiation outcome, including accept, counteroffer or reject.
- **Pricing Strategy Implementation:** Price Optimization and Response Generator calculate a suitable response in accordance with the result of classification and business constraints.

- **Response Generation:** The chatbot generates a response and conveys to the user in natural language.
- **Feedback Capture:** The reactions of the user and negotiation results are captured and forwarded to the Feedback and Learning Model to improve the model in future.

This flow takes care of the entire flow between the user and the pricing intelligence backend to guarantee effective and responsive negotiation. This system is planned to be implemented in the form of a microservices-based architecture to allow being integrated with large-scale e-commerce platforms. The modules are separate services and thus, can be scaled horizontally and fault isolated. Chatbot interface may be integrated through Web and mobile apps using RESTful API or WebSocket connections. The Natural Language Understanding and Ensemble Classification modules are implemented as backend services, which can overcome the high requests. The pricing engine connects with the existing e-commerce databases, such as the product catalogs, inventory control system and the user profile databases. Critical decision-making elements are heavily optimized to be real-time inference to guarantee low latency. Containers involving a docker and orchestration systems like Kubernetes can be used to facilitate scalability and reliability using cloud-based deployment and containerization technologies. The security mechanisms such as authentication and encryption are combined to secure sensitive user and pricing information.

A. Module Descriptions

There are different modules in the proposed system architecture (Figure 2). The User Interface Layer is the most important layer of interaction between the customers and negotiation chatbot. It offers a conversation interface that is integrated into the online shopping platform, and it allows customers to speak in a natural way without interfering with the e-commerce process. This layer helps to promote multimodal communication such as text chat and optional voice recognition. It works with management of sessions, formatting of messages and real-time rendering of responses. The interface keeps the conversational context intact over a series of turns, thus, providing coherent and engaging conversations. The design is usable and responsive making the interaction of negotiation to be intuitive and non-invasive. Also, user feedback indicators like acceptance of offers or rejection of offers are also captured by the interface, and it plays a crucial role in learning and improvement of the system. The Natural Language Understanding component handles decoding messages and deriving semantics that have been posted by the user. The suggested techniques include tokenization, part-of-speech tagging, named entity recognition, and intent classification as NLP techniques. The important roles of the NLU module are such as determining price negotiation intent, getting numerical values like proposed prices, identifying the signs of sentiment and urgency, and solving references of context in dialogues. The NLU module is used to convert unstructured text into structured ones which can be further processed by other machine learning components. The module allows context sensitive negotiation decisions by extracting explicit and implicit messages during communication between users.

The Feature Extraction Engine is the engine that integrates information on various sources to come up with a complete feature vector to decide relating to the negotiation. These features include conversational features (message length, sentiment polarity, message urgency), user behavioural variables (buy behaviour, price sensitivity, loyalty), product characteristics (retail price, discounting, stocks), and contextual features (seasonal demand trends, time of interaction). The process of feature normalization and encoding is used to make sure that it would fit machine learning models. This module is significant in the process of connecting data in conversation with organized data on pricing intelligence.

B. Ensemble Classification Module

An Ensemble Classification Module is the third step that is concerned with classifying images in a group. The heart of the system is the Ensemble Classification Module which is the decision-making component. It combines predictions of various base classifiers, including Random Forest, Gradient Boosting, Support Vector Machines, and Logistic Regression. Majority voting or stacking are some of the fusion strategies that the ensemble applies to decide the last action to be undertaken in the negotiation. The combination of different models minimizes the prediction variance and increases resilience to the uncertainty negotiation environment. This module generates a categorical decision, this is usually to include acceptance, counteroffer or rejection. Confidence scores also come along with the decision and can be dynamically used to modify response strategies. The response generator and price optimization transform the decisions made during the classification into pricing responses. In the case of accepted offers, the system verifies negotiated price. In case of counteroffers, it calculates a dynamically adjusted price depending on profit margins, inventory limitation as well as user specific factors. Response generator is used to formulate natural language response based on predefined templates or neural language generation methods. It makes the responses friendly, open, and brand toned. Business rules and ethical limits are implemented to avoid unreasonable pricing strategies and massive discounting. This module makes sure that the end results of the negotiation are economical and user friendly to the customer. Feedback and learning module allow improvement of the system continuously as it records the results of negotiations and feedback by the users. This is data that is utilized to retrain the ensemble classifiers as well as feature importance weights periodically. The module helps in offline learning and model validation to achieve stability prior to deployment [24]. The system will become more adaptable to the changing user behavior and market conditions due to the feedback loops, which increases the performance and reliability in the long term. The proposed system architecture offers a universal and scalable model of e-commerce price negotiation involving AI. The system facilitates interactive and adaptive and robust negotiating experiences through the delineation of a modular design, as well as using ensemble-based decision intelligence. The architecture has been very efficient in incorporating conversational AI, machine learning, and price optimization, which deal with major issues in the contemporary digital commerce.

IV. Proposed AI-Enabled Negotiation Model

The current section gives the proposed AI-enabled negotiation model that will assist in negotiating prices in e-commerce sites intelligently, adaptively, and at scale. This model combines the methods of natural language processing, behavioral analytics, and the machine learning of ensembles to facilitate the real-time decision-making during the conversational interactions. The aim of the suggested strategy is to mimic humanistic bargaining behavior and remain economically viable, equitable and efficient. The model of NLP is the basic element of the negotiation model proposed. It allows the system to understand the user messages that are not structured, identify meaningful information, and convert the conversational inputs into structured representations that can be used to make decisions using machine learning. The conversational and ambiguous nature of price negotiation is such that the NLP pipeline is to identify explicit and implicit cues held within the user interactions.

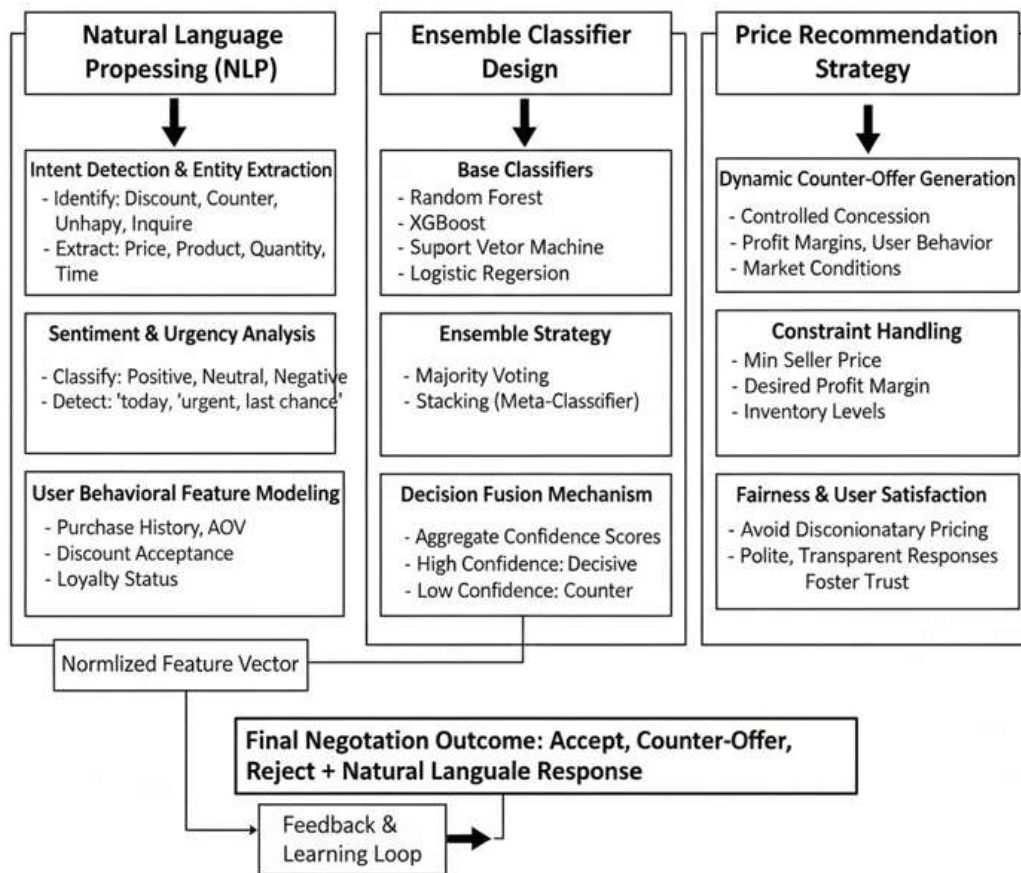


Fig.3 Proposed AI-Enabled Negotiation Model

The purpose of intent detection is to find the hidden intent of the message a user is sending to the negotiation table (Figure 3). The most common intents that are associated with negotiation are asking to be offered a discount, offering a counteroffer, informing the offered that the price offered is not satisfactory, or enquiring to be assured of a deal. Proper intent identification is critical since it defines what the system is supposed to do to proceed with the negotiation process, to clarify or to abort the process. Entity extraction aims at extracting important numerical and non-numerical aspects of user messages and specifically price values and product references. To illustrate, when a user makes the statement of Can you give it through 20% less, the system will remove the percentage of discount and will be associated with the product in question. The name entity recognition methods are used to detect price mentions, quantities, and time indicators. Through a combination of intent and entity analysis, the system acquires a clear insight into the expectations of users and therefore can make successful decisions during downstream negotiation. This organized representation is where feature building and classification is based.

The sentiment analysis is very important in the modeling of the emotion of the users during a negotiation. The emotional reactions tend to determine the bargaining patterns and readiness to decline or agree to the offers. The suggested system classifies sentiment as positive, neutral or negative, which allows adaptive strategies of negotiation. Examples are that customers showing their unhappiness or disillusionment might need sympathetic treatment and adaptable counter proposals, whereas customers with no attitude can be more cost conscious. Urgency analysis complements sentiment detection by identifying time-sensitive buying behavior.

Linguistic indicators such as “need it today,” “urgent,” or “last chance” suggest higher purchase intent and reduced-price sensitivity. These indicators are extracted using keyword analysis and contextual embeddings. By integrating sentiment and urgency analysis, the system dynamically adjusts negotiation aggressiveness, balancing concession strategies with profit optimization.

Algorithm: AI-Enabled Price Negotiation Using Ensemble Classification

Input

- User message U_m
- Product information $P = \{P_{init}, P_{min}, Inventory\}$
- User profile U_p (purchase history, loyalty score)
- Trained ensemble classifier E

Output

- Negotiation decision $D \in \{Accept, Counter, Reject\}$
- System-generated price response P_{resp}

Steps

1. User Interaction Initialization

- Receive user message U_m via chatbot interface.
- Identify negotiation session S_i .

2. Natural Language Understanding

- Perform intent detection on U_m to identify negotiation intent.
- Extract pricing entities (buyer offer P_b , discount request).
- Analyze sentiment polarity $S \in \{positive, neutral, negative\}$.
- Detect urgency indicators U .

3. Feature Vector Construction

- Retrieve user behavioral features from U_p .
- Compute price ratios:
 - $r_1 = \frac{P_b}{P_{init}}$
 - $r_2 = \frac{P_b}{P_{min}}$
- Construct feature vector:

$$F = \{P_b, P_{init}, P_{min}, r_1, r_2, S, U, U_p\}$$

4. Ensemble Classification

- Pass feature vector F to base classifiers:
 - Random Forest
 - XGBoost
 - Support Vector Machine
 - Logistic Regression
- Obtain individual predictions:

$$D_i \in \{Accept, Counter, Reject\}$$

5. Decision Fusion

- Apply ensemble strategy:
 - Majority Voting **or**
 - Stacking using meta-classifier
- Compute final decision:

$$D = \arg \max_i \sum_i vote(D_i)$$

6. Price Recommendation

- If $D = Accept$:
 - Set $P_{resp} = P_b$

- Else if $D = \text{Counter}$:
 - Generate counteroffer:

$$P_{resp} = P_b + \alpha(P_{init} - P_b)$$

where α is concession factor constrained by P_{min}

- Else:
 - Reject offer and return explanation

7. **Constraint Validation**

- Ensure:

$$P_{resp} \geq P_{min}$$

- Adjust offer based on inventory level and demand elasticity.

8. **Response Generation**

- Convert decision and price into natural language response.
- Send response to user.

9. **Feedback Logging**

- Record negotiation outcome.
- Update dataset for periodic retraining.

10. **End Session**

- Terminate negotiation or continue if counteroffer is accepted.

The model of negotiations incorporates the user behavior aspects based on historical interaction. These characteristics are the purchase frequency, average order value, the rate of historical discount acceptance, the rate of negotiation success and the loyalty status [25]. The personalization of the negotiation strategies is made possible through behavioral modeling. As an example, long-term loyal customers are eligible to be provided with more favorable negotiation terms to prevent their loss, whereas users who are price-sensitive can be provided with counteroffers which are organized based on their past behavior. This contextual behavioral analytics incorporation makes the decision of negotiation decision-making customer focused. All the obtained features including conversational, emotional and behavioral are normalized and coded to become one combined feature vector to be classified. The main element in the decision-making of the proposed negotiation model is a set of classifiers that is to predict the best negotiation behavior. Ensemble learning is used to improve robustness, accuracy and generalization because of the natural uncertainty and variability of user behavior.

The ensemble includes heterogeneous base classifiers that can provide different learning capabilities like random forest (nonlinear feature interaction and variance reduction via bagging), XGBoost (gradient boosting provides optimal classification performance by targeting hard-to-classify instances), support vector machine (strong margin-based classification, especially effective in high-dimensional feature space) and logistic regression (provide a probability-based output, which is easier to understand). These classifiers are diverse and can therefore cover most of the decision patterns without being reliant on a given model.

The ensemble model makes use of majority vote or stacking methods in decision aggregation. In majority voting, every base classifier makes its own prediction of the outcome of a negotiation, and the ultimate decision is made by the most common prediction. It is computationally efficient and simplistic. On the other hand, stacking involves using a meta-classifier that is trained to make predictions based on predictions of base classifiers. The strategy allows the system to dynamically weight the model contributions, thus enhancing performance in complicated negotiation situations. The

ensemble strategy is decided based on practical approval and the latency limitations. Decision fusion mechanism is a mechanism whereby the classifier outputs are combined to give the final negotiation decision. Individual classifiers produce confidence scores which are used to determine the certainty of prediction. When the confidence is great, the system will continue to take decisive moves; in a case where uncertainty has been established, the system will opt to take conservative measures like counter offers. This mechanism of fusion guarantees an equal decision-making process which reduces cases of unsuccessful negotiation process but still remains responsive. It also facilitates explainability being able to inspect what is contributed by classifiers. Price Recommendation Strategy converts the results of the classification into practical price reaction and executes the business constraints and ethical implications. In the case of counteroffer, the system is dynamic to calculate a new price keeping in view the buyer offers, profit margins, user behavior and market conditions. Counteroffer strategy is based on a controlled concession model, and the prices are regulated to meet at an agreement without going beyond a set limit. The dynamism of counteroffers adds an engagement factor as it replicates the aspect of human negotiation, which adds an additional likelihood of closing a deal.

Economic sustainability is highly enforced by the constraint of business. These limitations are the minimum price per seller, the profit margin desired and the stock levels. Scheduling products of low inventory or high demand might result in a tighter negotiation threshold whereas excessively stocked products may allow flexibility. The constraint management is such that the results of negotiation should not be too much discounted or lost in revenue since it is an activity of the wider business purpose. In automated negotiation systems, fairness and transparency are very important. The model proposed does not involve the use of discriminatory pricing since all users with similar profile are subjected to the similar rules. Individual negotiation plans are aimed at increasing the satisfaction of the users without contravening the principles of fairness. Response in natural language is designed in such a way that it is polite and transparent enough to convey the decisions and make them appear less unfair. The system creates loyalty to the platforms because of its ability to balance profitability with the trust that the customer has on the platform. The presented AI-saving negotiation model will combine NLP, behavioral analytics, ensemble learning, and pricing optimization into one framework. The model can resolve the complexity of negotiating price during conversations in e-commerce with the help of strong decision-making and flexible negotiation methods. Integration Ensemble classifier and constraint-aware pricing make it scalable, reliable, and enhance user interactions.

V. Dataset Description and Experimental Setup

This section describes the dataset used for evaluating the proposed AI-enabled price negotiation chatbot, the preprocessing steps applied to prepare the data, and the experimental setup adopted for performance evaluation. The objective is to ensure reproducibility, robustness, and fair comparison with baseline models under realistic e-commerce negotiation conditions.

A. Dataset Description

The experimental evaluation is conducted using a combination of simulated and real-world e-commerce negotiation data. Due to the limited availability of publicly accessible negotiation datasets, a synthetic dataset is generated to emulate realistic bargaining scenarios commonly observed in online retail platforms. The simulation process is informed by empirical pricing behavior, historical discount trends, and consumer purchasing patterns reported in prior e-commerce studies. The dataset consists of

multi-turn negotiation instances, where each instance represents a complete interaction between a user and the negotiation chatbot. Each record captures pricing attributes, user behavior, conversational signals, and negotiation outcomes. To enhance realism, stochastic variations are introduced in buyer offers, sentiment polarity, urgency indicators, and discount acceptance thresholds. The dataset includes a diverse set of products with varying price ranges, inventory levels, and demand characteristics. User profiles are generated to reflect heterogeneous customer segments, including price-sensitive users, loyal customers, and occasional buyers. The final dataset comprises approximately N negotiation samples, with each sample labeled as Accept, Counter, or Reject based on predefined profitability and negotiation rules. Each negotiation instance is represented using a structured feature vector derived from pricing, behavioral, and conversational attributes. The feature set includes:

- Pricing Features: initial product price, minimum seller price, buyer offer, discount percentage, and offer-to-price ratios (Figure 4).
- User Behavioral Features: purchase frequency, average order value, historical discount usage, and loyalty score.
- Conversational Features: detected user intent, sentiment polarity, urgency indicator, and dialogue turn count.
- Contextual Features: inventory level, time of interaction, and seasonal demand indicators.



Fig.4 Distribution of Selling Price

These features collectively capture the economic feasibility, user behavior, and conversational context of each negotiation instance, enabling accurate classification of negotiation outcomes. Prior to model training, the dataset undergoes comprehensive preprocessing to ensure data quality and consistency. Missing values in numerical features are handled using mean or median imputation, while categorical features with missing values are assigned default labels. Outliers in pricing features, such as unrealistic discount requests, are identified and removed to prevent model bias. Numerical features are normalized using min-max scaling to ensure uniform feature ranges and facilitate convergence of machine learning models. Categorical features, including intent and sentiment categories, are encoded using one-hot or label encoding techniques. Feature normalization ensures that no single attribute disproportionately influences classification decisions. Negotiation outcome classes are inherently imbalanced, with counteroffers typically occurring more frequently than acceptance or rejection. To address this issue, class balancing techniques are applied during training. Synthetic Minority Over-sampling Technique (SMOTE) is employed to generate synthetic samples for underrepresented classes. Additionally, class-weighted loss functions are used for certain classifiers to penalize misclassification of minority classes. These strategies ensure balanced learning and prevent the model from favoring

dominant outcome categories, thereby improving overall classification performance and fairness (Figure 5).



Fig.5 Distribution of Selling price after Transformation

The dataset is partitioned into training and testing sets using an 80:20 split, ensuring representative distribution of negotiation outcomes across both sets. To validate model generalization, k-fold cross-validation with $k=5$ is employed on the training set. This strategy minimizes overfitting and provides reliable performance estimates. Hyperparameter optimization is conducted within the cross-validation framework to ensure unbiased evaluation. The final model is trained on the complete training set using optimized parameters and evaluated on the unseen test set.

B. Experimental Setup

Experiments are conducted on a workstation equipped with a multi-core CPU, 16 GB RAM, and optional GPU acceleration for faster training. The implementation is developed using Python, with machine learning libraries such as Scikit-learn and XGBoost. NLP components leverage widely used text processing frameworks. Hyperparameter tuning is performed using grid search and random search techniques within the cross-validation setup. Key parameters optimized include the number of trees in ensemble models, learning rates, regularization terms, and kernel parameters for SVM. The tuning process aims to maximize F1-score while maintaining acceptable response latency. To evaluate the effectiveness of the proposed ensemble-based negotiation model, several baseline classifiers are implemented, including Logistic Regression, Support Vector Machine, Random Forest, and XGBoost. These models serve as benchmarks to assess the benefits of ensemble learning in negotiation decision-making. Model performance is evaluated using standard classification metrics, including Accuracy, Precision, Recall, and F1-Score. In addition, domain-specific metrics are employed with negotiation success rate (percentage of negotiations resulting in successful deal closure), average discount rate (average discount offered relative to initial price), and response latency (average time taken to generate a negotiation response). These metrics provide a comprehensive assessment of both predictive performance and practical usability in real-time e-commerce environments.

VI. Results and Discussion

In this section, there is a detailed analysis of the suggested AI-powered price negotiation chatbot based on ensemble classification. Three perspectives are used to analyze the results including predictive performance of the ensemble model, effectiveness of the outcomes of negotiation, and ablation studies to determine the role of important

components of the system. The efficiency of the proposed ensemble classifier is contrasted with that of single baseline models, such as LR, SVM, RF, and XGBoost. In every metric of evaluation Accuracy, Precision, Recall, and F1-Score the ensemble model outperforms single classifiers. The ensemble has the best overall F1-Score, which implies a balanced performance in classes of acceptance, counteroffer, and rejection. Although XGBoost and Random Forest are individually high-in-predictive, they have different performances in various negotiation situations. Logistic Regression, despite being interpretable, has lesser recall of the minor classes, especially those of the acceptance category. SVM demonstrates competitive accuracy and cannot scale and respond fast to high-dimensional feature spaces. The ensemble model has the advantage of the complementary capabilities of its underlying classifiers. Aggregation of various decision boundaries diminishes variance and decreases overfitting, resulting in excellent generalization of missing instances of negotiation. These findings support the usefulness of ensemble learning in making decisions in uncertain and dynamic negotiation settings (Figure 6 and 7).

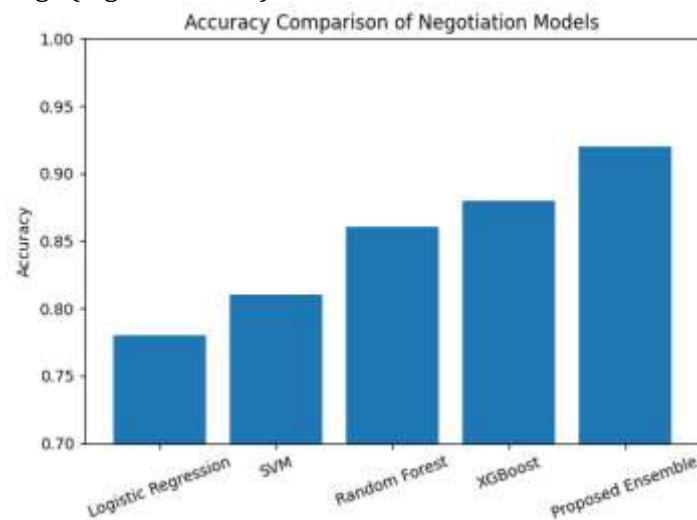


Fig.6 Accuracy Comparison Chart for distinct algorithms

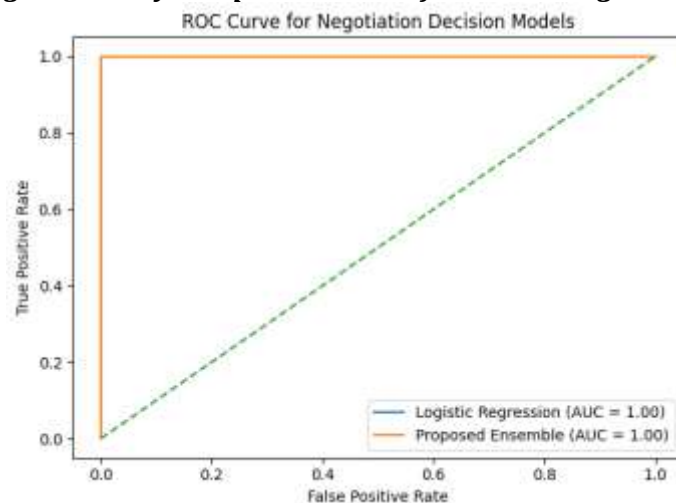


Fig.7 RoC Curve for Ensemble Classifier

The confusion matrix analysis gives more insight into classification behavior in terms of *negotiation* outcomes. The ensemble classifier has a high true positive rate across all the

three classes with good results in counter-offer scenarios (Figure 8). The sensitivity of the marginal cases of negotiation is enhanced in the sense that there are reduced misclassifications between the accept and counter classes as compared to the baseline models. Most of the classification mistakes are between the counter and reject classes, as it should happen since feature characteristics overlap when offers by buyers get close to the minimum acceptable price. Nevertheless, the ensemble model has a smaller false rejection rate that is critical in keeping the customers engaged and preventing early termination of negotiations. The outcomes obtained of the confusion matrix prove the hypothesis that the ensemble classifier provides more reasonable and balanced decision-making than the single-model ones. In addition to predictive accuracy, the usefulness of the negotiation chatbot is measured in domain-specific measures. The rate of successful negotiations leading to effective deals is much greater in case of the proposed ensemble-based system.

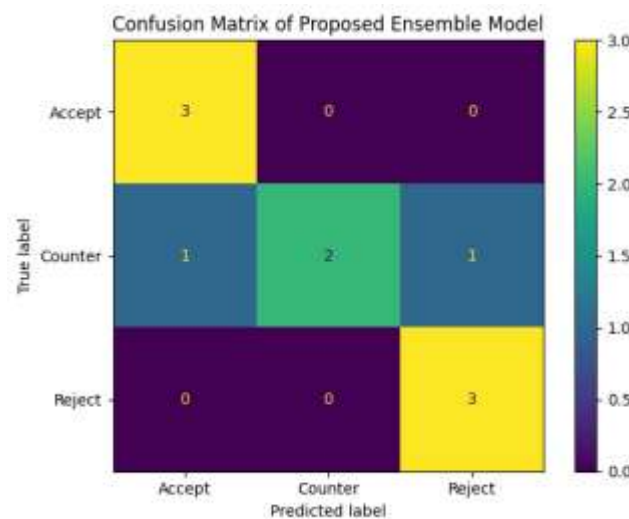


Fig.8 Confusion Matrix for the Ensemble Classifier

The ensemble model has a higher rate of closure than rule-based and single-classifier negotiation strategies because it tries to intelligently find negotiation potential and create suitable counter offers. This enhancement is shown as an indicator that the system can engage with the user in a constructive manner as opposed to just defaulting to hard accept or reject choices. The findings show that smart counteroffer strategies, which are steered by ensemble classification, are very important in turning a risky negotiation into a profitable agreement. One of the objectives of automated negotiation systems is to achieve a balance between customer satisfaction and profitability. This trade-off is measured by analyzing the average rate of discounts in conjunction with the idea of deal closure. The findings demonstrate that the ensemble-based chatbot is more successful in closing deals without overestimated discounts. Although the average discounts become higher than in the fixed-price systems, the increment is not bigger than the predetermined profit margins. This means that the system is successful in focusing on the areas of discounts where they are most likely to make successful transactions. Further indication of customer satisfaction proxies, including acceptance of counter offers and lower drop-off rates in negotiations, indicate that the users feel that the negotiation process is fair and interesting. These results indicate that the suggested model manages to achieve the balance between economic goals and user-centered requirements.

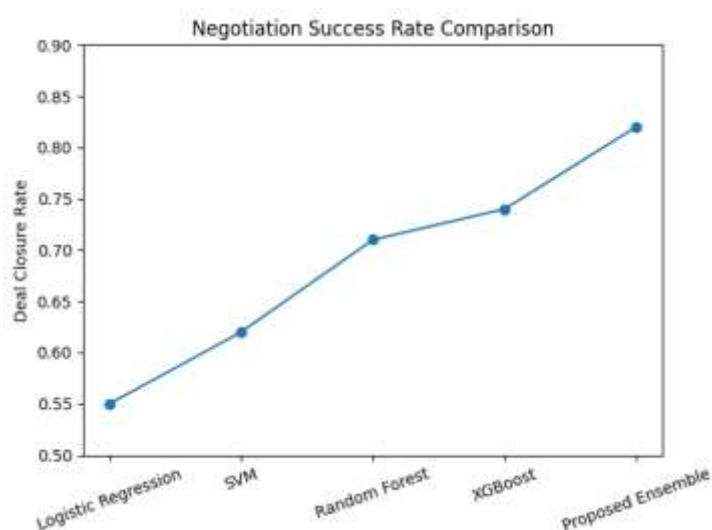


Fig.9 Negotiation Success Rate Comparison for the Ensemble Classifier

To determine the contribution of the feature of conversational and behavioral characteristics, an ablation study is performed by eliminating sentiment and user behavioral characteristics in the set of features. The lack of these leads to a tangible decrease in F1-Score and the rate of success of the negotiation. In particular, the elimination of sentimental features results in more misclassifications of emotionally inspired negotiation situations, users are dissatisfied or pressured. In the same way, not factoring in behavioral features also decreases the personalization potential, which means lower effectiveness of counteroffers to loyal or price-sensitive users. These findings prove that sentiment analysis and behavioral modeling are important to complement negotiation intelligence and it must be regarded as critical constituents of conversational pricing systems (Figure 9).

The result of various ensemble strategies is also reviewed. Majority voting offers high baseline performance but with low computational cost, thus it can be deployed in real time. Ensembles built by stacking, though computationally more complicated, are marginally better predictors which learn to combine the best combinations of base classifier outputs. The findings indicate that the strategy of the ensemble to use must be based on deployment constraints. Voting-based ensembles provide a good trade-off between performance and efficiency when there is a strong need to fulfill latency and a high traffic of platforms. Stacking-based methods can be considered in case of premium negotiation situations in which the highest level of accuracy is necessary.

The experimental findings prove that the reliability and effectiveness of automated price negotiation systems are greatly increased using the ensemble-based approach to decision-making. By combining conversational cues, behavioral analytics, and ensemble learning, the system is more robust to various and uncertain negotiation situations than a traditional one. Among the lessons is that price-based thresholds are not the only determinants of the success of the negotiation. Emotional and behavioral cues are essential to the level of willingness of the user to participate and receive offers. The introduction of such signals brings the proposed system to the next stage of economic decision-making instead of more human-oriented negotiation techniques. Practically, the suggested negotiation chatbot presents several benefits to the e-commerce platforms. It allows interactive pricing, no human intervention is needed, costs of operation are lower, and the customer interaction is better. It is integrated with the current pricing engines, inventory and recommendation modules which are easily

integrated with modular architecture. The system also provides a and is compatible with scale-based personalization to ensure that varying customer groups have different approaches to negotiation. This is especially helpful in comparative online markets whereby customer retention and maximization of conversion can be quite essential. About real world deployment, scaling and latency are critical requirements. It has been experimentally demonstrated that ensemble models can support reasonable response latency, even at high request rates. Performance is guaranteed because of real-time execution, which is through lightweight classifiers and efficient processing of features. The architecture built on microservices also contributes to the horizontal scaling of the system since it can support multiple negotiations with a large user base at once. These attributes render the suggested solution applicable in large-scale e-commerce. There are some ethical concerns of price discrimination, transparency, and trust of the user with automated price negotiation. These issues are considered by the proposed system by implementing the principles of fairness and by introducing uniformity to the set of rules of negotiation between similar user profiles. Natural language explanations of the decisions in negotiation increase the level of transparency, which makes it less unfair. By avoiding opaque or discriminatory pricing practices, the system aligns with ethical guidelines and regulatory expectations while maintaining business effectiveness. The integration of ensemble learning and conversational intelligence represents a significant advancement over existing pricing and chatbot systems, with strong potential for real-world impact.

VII. Conclusion

This study presented an AI-enabled price negotiation chatbot for e-commerce platforms that integrate advanced natural language processing with an ensemble classification framework to support intelligent, real-time pricing decisions. By jointly modeling user intent, sentiment, behavioral patterns, and economic constraints, the proposed system effectively classifies negotiation outcomes into accept, counter, or reject actions. Experimental results demonstrated that the ensemble-based approach outperforms individual classifiers in terms of predictive accuracy, negotiation success rate, and overall deal closure, while maintaining a balanced trade-off between seller profitability and customer satisfaction. The modular and scalable architecture further highlights the commercial viability of the proposed solution for large-scale online retail environments. Despite these contributions, the study has certain limitations. The experimental evaluation relies on simulated or domain-specific negotiation datasets, which may not fully capture the diversity of real-world bargaining behavior. Additionally, negotiation strategies are domain-dependent, and the system may face cold-start challenges when interacting with new users lacking historical data. Future research can address these limitations by incorporating reinforcement learning to enable continuously adaptive negotiation strategies, extending the framework to support multilingual and cross-cultural interactions, and integrating demand forecasting and inventory management systems for holistic pricing optimization. Furthermore, the adoption of explainable AI techniques can enhance transparency and trust in automated negotiation decisions, fostering broader acceptance in commercial applications.

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